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Predicting Avalanche Intensity from Weather Data: A Statistical Analysis

by Arthur Judson
and Bernard J. Erickson

Abstract

Nineteen weather factors were analyzed to determine which have the highest correlation with avalanche activity. A simple two-parameter storm index and a discriminant function model were found to predict the likelihood of avalanches in Colorado's Front Range. The storm index utilizes precipitation intensity modified by windspeed to predict the number of avalanches expected on 23 paths. The discriminant function model was used in conjunction with a multiple regression program to classify snow as stable or unstable on eight avalanche paths. This analysis shows that a linear combination of the maximum 3-hour precipitation intensities, windspeed resolved to an optimum direction for each path, and the sum of the negative temperature departures from 20° F could be used to determine whether a slope will avalanche 70 to 80 percent of the time.

Oxford: 384.1:423.5. **Keywords:** Avalanches, weather, snow, statistical analysis, statistical methods.

ALL PHOTOS,

SEVEN SISTER AVALANCHE PATHS,

MAY 3, 1973:

This slab avalanche released at 4 a.m., following intense snowfall, strong winds, and cold temperatures. All seven of the north-facing Seven Sister paths discharged their snow cover simultaneously.

The fracture line, estimated as 10 feet high in the smooth curved section, extended across gullies and straight slopes for half a mile beyond the area shown at right edge of the centerfold photo.

The tongue-shaped snow layer, barely discernible left of the debris blocks (near center of centerfold photo), probably was the bed surface of a previous avalanche.

The snow that ran down the No. 6 2,000-foot track was 12 feet deep on U.S. Highway 6.

Traffic was minimal, and no injuries or damage resulted.

An event of this magnitude rarely occurs in the Seven Sister area.

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Contents

Predicting Avalanche Intensity from Weather Data: A Statistical Analysis

Arthur Judson and Bernard J. Erickson

Avalanche personnel know that certain weather factors contribute to avalanching, but determining the relative contribution of various factors is difficult for several reasons. For one thing, most statistical analyses are complicated by the high correlations between factors. Also, good weather and avalanche data are rare because they must be continuously monitored in a severe environment, and the complexity of the relationship between weather and avalanches requires a long, continuous record. Finally, even though avalanche researchers agree that precipitation, wind, and temperature influence snow stability, they do not agree on the best methods of quantifying these and other factors for forecasting purposes. The objectives of this study were to select weather factors that dominate avalanche response, evaluate their relative contribution, and develop a predictive model.

Weather data for the study were collected at Berthoud Pass in Colorado's Front Range from 1951 to 1972. Avalanche records were collected for the same time period. Weather records were taken by the Forest Service; avalanche data were collected by the Forest Service, Colorado Department of Highways, and American Metals Urad-Henderson Mines. The following weather data were put on magnetic tape to facilitate analysis and to insure a convenient permanent file: maximum 3-hour precipitation intensity, 6-hour average windspeed and direction, temperature and temperature trends, 24-hour new snowfall, water equivalent, total snow depth on the ground, and temperature extremes. Data format for both weather and avalanches is identical to that used by stations on the Forest Service weather and avalanche reporting network (Judson 1970).

For a first approximation, weather and avalanche data from 23 avalanche paths were analyzed by univariate techniques similar to Perla's (1970) analysis of contributing factors in avalanche hazard evaluation. This univariate analysis resulted in a relatively simple two-parameter storm index that effectively predicts the number of avalanches expected on the 23 paths. Thirteen factors isolated in the univariate analysis were subsequently subjected to a multivariate discriminant function analysis to produce a more refined three-variable model to predict the likelihood of avalanches on eight paths. This model will be thoroughly evaluated and further refined in the coming avalanche season.

The Univariate Analysis

Seven winters of data (1963-70) were used in this phase of the study. Twenty-three avalanche paths located in the Central Rockies near Berthoud Pass, the Urad Mine, and Loveland Pass were selected for analysis (table 1). Avalanche records for these paths were uniformly good, and the group had terrain features representative of most paths in the Front Range. Nineteen paths in this group were controlled by explosives. The group included moderate- and high-frequency paths which produced an average total of 93 avalanches per winter during the 8 winters, 1963-71.

Scatter diagrams and linear regression proved useful in delineating important weather factors. The number of avalanches from the 23 paths was plotted as a function of single weather factors or simple combinations of them during 42 storms. Storms were defined on the basis of precipitation episodes during the months of December through March. The beginning of a storm was defined as a time when measurable precipitation fell in two consecutive 6-hour periods. A storm was considered over when precipitation ceased for three or more consecutive 6-hour periods.

Table 1.--Some features of the 23 avalanche paths (19 controlled) used in the univariate analysis, 7 winters of data (1963-70)

Path name	Location	Starting zone aspect	Vertical drop	Events recorded, 1963-71: Path frequency per winter	Events recorded, 1963-71: Controlled during period
		Degrees	*Feet*	*Number*	*Percent*
Lift Gully	Berthoud Pass Ski Area	100	360	16	94
Seven Sister 1	U.S. 6	05	600	6	56
Seven Sister 3	U.S. 6	360	640	7	64
Seven Sister 7	U.S. 6	360	750	2	81
Four B	Urad Mine	105	1,840	4	89
Northwest Red	Urad Mine	350	1,840	5	74
Roll	Berthoud Pass Ski Area	80	350	4	66
Five A	Urad Mine	125	1,600	4	68
Five B	Urad Mine	165	1,810	3	75
Current Creek	Berthoud Pass Ski Area	85	500	8	0
Stanley	U.S. 40	160	2,760	3	54
Four A	Urad Mine	90	1,840	4	90
South Chute Roll	Berthoud Pass Ski Area	30	350	3	74
One C	Urad Mine	160	2,120	2	72
One E	Urad Mine	170	1,900	4	81
Bethel	U.S. 6	160	2,200	3	14
Dam	U.S. 40	70	2,600	3	0
Five C	Urad Mine	360	1,840	2	71
Five Car	U.S. 6	75	400	2	33
Little Professor	U.S. 6	140	1,360	2	27
Floral Park	U.S. 40	290	920	2	8
Black Widow	U.S. 6	160	1,640	2	17
Berthoud Falls	U.S. 40	05	2,440	2	0

Some weather factors, such as total water equivalent (fig. 1), showed definite trends while others showed little or no relation to avalanche activity (fig. 2). Several factors were eliminated on this basis. Weather factors tested against avalanche occurrence by scatter diagrams and linear regression during 42 storms were:

Factors kept for further analysis
1. 24-hour water equivalent.
2. 24-hour snowfall.
3. Maximum precipitation intensity.
4. Maximum precipitation intensity modified for excessive wind.

Factors rejected from further analysis
1. Average windspeed.
2. Sums and cross products of maximum precipitation intensity and windspeed (several combinations).
3. Temperature change during storms.
4. New snow density.
5. Settlement.

Wind direction was not analyzed during this part of the study because the paths had many aspects, and wind direction varied considerably during single storms. Much of this variation was due to the approach and passage of upper level troughs. The usual sequence was from SW to W to NW.

The Storm Index

Factors kept for further analysis were subjected to regression analysis using data from 81 storms during 1963-70. The factor best correlated with avalanche activity was the sum of the maximum precipitation intensities multiplied by a constant for excessive windspeed. This factor ($\Sigma\dot{P}k$), termed the **storm index**, predicts the total number of avalanches (controlled or natural) expected on the 23 paths as the result of a storm. For existing data, the

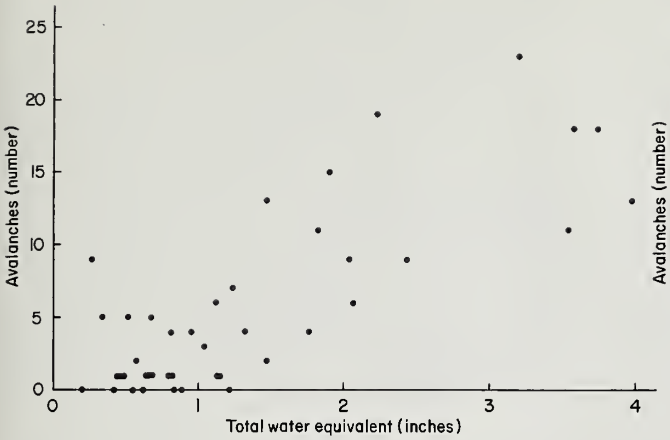

Figure 1.--Number of avalanches from 23 paths as a function of the 24-hour water equivalent of newly fallen snow, 7 winters, 1963-70.

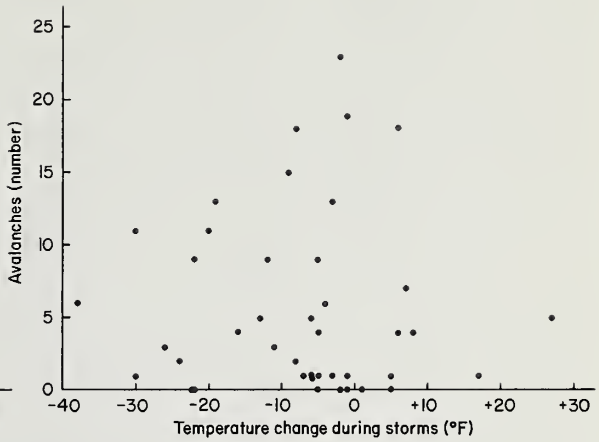

Figure 2.--Number of avalanches from 23 paths as a function of the temperature change during storms, 7 winters, 1963-70.

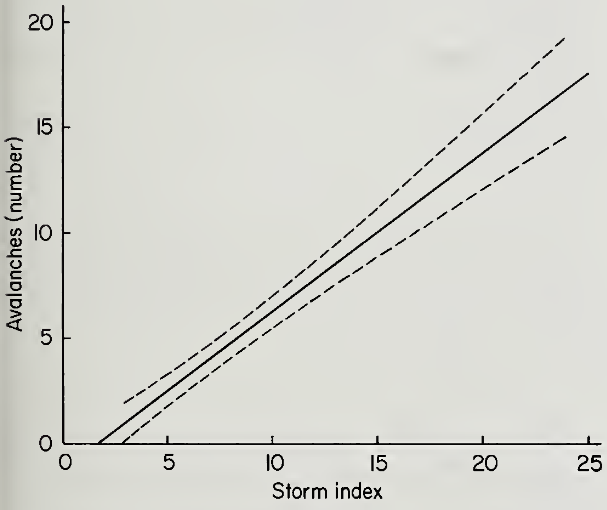

Figure 3.--The storm index, with 95 percent continuous confidence intervals for the mean of all future observations. The number of avalanches expected, based on 7 winters' data, 1963-70, on the 23 paths =

$$\hat{Y} = -1.31 + 0.76\ [\Sigma_1^n\ \dot{P}k]$$

where:

n = number of 6-hour periods in a storm;

$\dot{P}$ = maximum 3-hour precipitation intensity within each 6-hour period;

k = a constant.

k = 1 with windspeeds < 27 m.p.h.

k = 0.3 with windspeeds ≥ 27 m.p.h.

The correlation coefficient r = 0.86.

index has a correlation r of 0.86 and a standard error of ± 2.7 (fig. 3).

The storm index is computed every 6 hours and requires minimum instrumentation—a recording precipitation gage and a continuous windspeed record give the required data. This index was developed with avalanche data from paths that have been reliable indicators of avalanche activity in the Loveland-Berthoud Pass areas west of Denver.

The storm index was tested on 20 storms during 1971-72 (fig. 4) with satisfactory results.

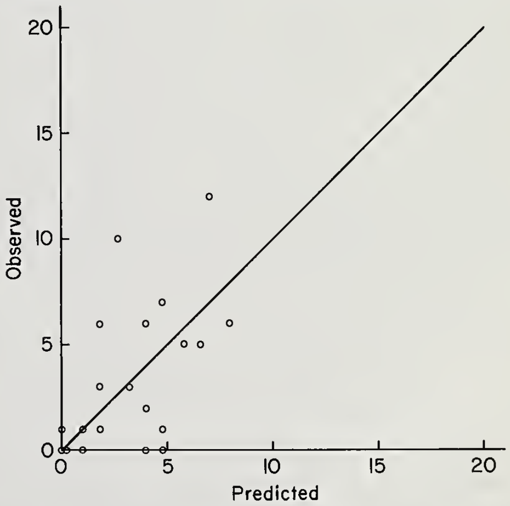

Figure 4.--Scatter diagram of observed versus predicted avalanches for 20 storms during 1971-72. Predictions based on the storm index derived from 1963-70 data.

The predicted numbers of avalanches fell within the confidence intervals shown in figure 3. Observed values were not consistently above or below the predicted, and scatter about the regression line appears to be random. Much of the scatter is attributed to nonuniform control efforts due to other operational considerations confronted by highway and mine personnel.

It was interesting to note that another storm index, developed with avalanche data from 23 uncontrolled avalanche paths, had a much lower correlation coefficient and a greater degree of scatter than the one we finally developed. This difference implies that forecasting indices based on avalanche data from uncontrolled paths are difficult to interpret and are less reliable as forecast guides.

The main drawback with the storm index is that the index is highest near the end of storms, even though hazard may be decreasing because some avalanches have already fallen and the snow is stabilizing. A way of reducing the index toward the end of the storm (a decay function) is badly needed and is now under study.

Applications

The storm index should have some application in other mountain areas. It utilizes precipitation intensity and windspeed during storms to predict the expected intensity of avalanching on an area basis. Because this index was developed using avalanche data from 23 paths that have a wide variety of physical features, we believe it will work, with some modifications, at most avalanche areas. The two weather factors comprising the storm index are directly related to the rate of loading on avalanche slopes. The rate of loading is a prime factor contributing to avalanche release at any area. Plans are being developed for testing the storm index at other avalanche areas.

The Multivariate Analysis

Weather factors other than precipitation intensity and windspeed affect avalanche formation. Moreover, because it is the combined effect of several factors which determines snow stability, it appeared logical to try a multivariate approach to predicting avalanche potential. Also, factors affect individual paths in different ways, so a single path analysis was indicated. A discriminant function analysis was selected for the second phase of the study.

A group of 10 well-defined, controlled paths (table 2) were selected for this analysis. Data from 1952-71 were analyzed. Like those in the first phase of this study, these paths run frequently, and data on their occurrence and control were uniformly good. They are representative of many moderate- to high-frequency paths in the Front Range because of their location, physical features, and wide variety of starting zone aspects. Eight paths threaten highways or roads, and two are in a ski area. None are skied.

The Discriminant Function

The discriminant function is a multivariate statistical technique of assigning data into two or more groups based on prior knowledge. More specifically, it is the linear component of p variables which maximizes the ratio of the between-groups variance to the within-groups variance.

In general form, the discriminant function is written as

$$L = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \qquad [1]$$

The discriminant coefficients $\beta_1, \beta_2 \ldots \beta_p$ are computed using the Fisher method discussed by Rao (1952). The multivariate mean of group 1 is given by

$$R_1 = \beta_1 \overline{X}_{11} + \beta_2 \overline{X}_{21} + \ldots + \beta_p \overline{X}_{p_1} \qquad [2]$$

and of group 2 by

$$R_2 = \beta_1 \overline{X}_{12} + \beta_2 \overline{X}_{22} + \ldots + \beta_p \overline{X}_{p_2} \qquad [3]$$

The generalized distance between the group means, called Mahalanobis' D^2, is the difference between the group means. Hence

$$D^2 = R_1 - R_2 \qquad [4]$$

The discriminant function is tested for significance using the F ratio involving D^2. When the function is significant, there is a real difference between groups. The discriminant index R_O, which determines the group classification of future data, is a weighted average of the group means:

$$R_o = \frac{n_1 R_1 + n_2 R_2}{n_1 + n_2} \qquad [5]$$

Table 2.--Pertinent features of the 10 avalanche paths (controlled) used in the multivariate analysis, 1952-71 data

Path name	Location	Starting zone			Vertical drop	Events recorded, 1963-71	
		Area	Aspect	Shape		Path frequency per winter	Controlled during period
		Acres	*Degrees*		*Feet*	*Number*	*Percent*
Lift Gully	Berthoud Pass Ski Area	0.2	100	Bowl-shaped depression	360	16	94
Cliff	Berthoud Pass Ski Area	0.4	90	Straight ramp	350	9	89
Floral Park	U.S. 40	10	290	Poorly defined, slight depressions with a midway bench	920	2	8
Stanley	U.S. 40	20	160	Broad bowl-shaped depressions and shallow gullies	2,760	3	54
Northwest Red	Urad Mine	22	350	Steep bowl-shaped depression with gullies	1,840	5	74
Four A	Urad Mine	10	90	Shallow gullies topped by a cliff	1,840	4	90
Four B	Urad Mine	15	105	Bowl-shaped depression with central gully	1,840	4	89
Bethel	U.S. 6	15	160	Straight slope feeding a gully from the side	2,200	3	14
Seven Sister 3	U.S. 6	0.5	360	Broad and shallow gully	640	8	64
Seven Sister 6	U.S. 6	4	360	Shallow depression flanked by a prominent rock rib	1,050	7	56

When $L > R_O$, the event is classified in group 1. The validity of R_O is attained by computing the probability of misclassification. This is done by entering D/2 in a cumulative normal frequency distribution table of the normal deviate.

The discriminant function was introduced by Fisher in 1938. It has since been used in medicine, psychology, engineering, biology, economics, anthropology, and geology. Weeks[2] was first to use the technique on weather and avalanche data. Bois and Obled [1972] recently began work with the discriminant function on data from Switzerland.

[2] *Unpublished data [1967], U. S. Army Materiel Command, Cold Regions Res. and Eng. Lab., Hanover, N. H.*

Analysis of Data

This study was confined to the period, November 15 to April 15, which limits the analysis to dry snow at this site. A 20-inch snow depth threshold at the Berthoud Pass weather and snow study site was required before analysis began. Data from 1952 through 1971 were used. Group classifications were based on control results. Snow was defined as unstable (group 1) when control efforts produced a slide or when a natural avalanche occurred. Snow was classified stable (group 2) when control efforts failed to initiate an avalanche. Weather data for both groups were limited to the interval between control applications and/or to the time between natural avalanches on each path. These intervals varied from 1 day to 6 weeks.

A preprocessing program (WXDAT) was written to select weather data for both groups from a master file of Berthoud Pass raw weather data on magnetic tape. WXDAT prepares an input file of selected weather variables for the discriminant function program. The program written by Davis and Sampson (1966) for the IBM 1620 was used in our analysis. This program was converted for use on a CDC 6400 computer at Colorado State University. The program avoids complex matrix inversion and computes the discriminant function coefficients for two groups with a maximum of 20 variables. Program outputs include the discriminant index R_o, the multivariate group means R_1 and R_2, the F ratio, and Mahalanobis' D^2. Additional outputs were added as analytical aids. The number of cases in each group does not have to be equal, but must exceed the number of variables.

Variates used with the program must not be highly interrelated, a constraint which presented an immediate problem since weather variables are correlated. Fortunately, a linear stepwise program could be applied to the discriminant problem due to the mathematical equivalence between the models. The correlation matrix provided by the stepwise program was used to delete highly interrelated variates which add little to the analysis.

For computational convenience, the stepwise program was given a dummied predictand as follows: Taking n_1 cases in group 1 and n_2 cases in group 2, we compute a predictand $n_2 \ / \ n_1 + n_2$ for all cases in group 1 and $-n_1 \ / \ n_1 + n_2$ for all cases in group 2. The average value of the predictand is zero since

$$n_1 \left[\frac{n_2}{n_1 + n_2}\right] + n_2 \left[\frac{-n_1}{n_1 + n_2}\right] = 0 \qquad [6]$$

Used in this manner, the stepwise or screening program provides a ranking of variates based on the increase in explained variance. The first variate is selected on the basis of having the highest F value at a given level. Once selected, it is held aside, and the program selects the variate with the highest F value of the remaining parameters, and so on. The screening program provides an unbiased selection of variates which are then run through the discriminant function program. The screening program is terminated when the additional variables entered are not significant.

The following 13 variables were selected for analysis on the basis of field experience and the earlier univariate analysis:

1. Sum of 24-hour water equivalents.
2. Sum of the maximum 3-hour precipitation intensities in each 6-hour period decayed over the interval.
3. Same as No. 2 without the decay function.
4. Sum of maximum precipitation intensities decreased for excessive windspeeds.
5. Count of 6-hour windspeeds < 15 m.p.h.
6. Count of 6-hour windspeeds between 15 and 27 m.p.h.
7. Count of 6-hour windspeeds > 27 m.p.h.
8. Count of 6-hour temperatures > 20° F.
9. Sum of the negative temperature departures from 20° F.
10. Average precipitation intensity.
11. Sum of windspeeds during precipitation periods, resolved to an optimum direction for each path.
12. Sum of windspeeds resolved to an optimum direction for each path.
13. Sum of squares of windspeeds resolved to an optimum direction for each path.

Results and Discussion

The discriminant function on 8 of the 10 paths was significant at either the 1- or 5-percent level. The avalanche records for the two paths failing the significance test were found to be incomplete because control teams failed to enter negative control results. Such data are critical since they define the time interval for weather data used in the analysis. Neither path provided a meaningful discriminant function.

Results of the study are summarized in table 3. The most important variates are:

No.	Designation	Variable
2	$\Sigma\dot{P}I^*D$	Sum of the maximum consecutive 3-hour precipitation intensities within each 6-hour period decayed over the interval.
9	ΣNeg TT	Sum of the 6-hour negative temperature departures from 20° F.
12	ΣVV_R	Sum of the windspeeds ≥ 15 m.p.h. resolved to an optimum direction for each path.

Maximum precipitation rates with a decay function ($\Sigma\dot{P}I^*D$) dominated avalanche response on five of the eight paths, while windspeed resolved to an optimum direction for each path

Table 3.--Composite summary of statistical data, multivariate analysis, 1952-71 data

Path (1)	Significance level (2)	Coefficient (3)	Variable symbol[1] (4)	Variable number[1] (5)	D^2 (6)	Probability of misclassification (7)	Increase in explained variance[2] (8)	R_o (9)
	Percent							
Lift Gully	1	0.011	ΣVV_{NW}	12	1.68	0.26	0.1907	2.26
		.280	$\Sigma \dot{P}I*D$	2			.0967	
		.000	ΣNeg TT	9			.0001	
Cliff	1	.416	$\Sigma \dot{P}I*D$	2	2.06	.24	.2904	3.37
		.004	ΣVV_{NW}	12			.0446	
Floral Park	5	.495	$\Sigma \dot{P}I*D$	2	2.50	.21	.3909	4.64
		.001	ΣNeg TT	12			.0126	
		.000	ΣVV_{NW}	9			.0021	
Stanley	1	.294	$\Sigma \dot{P}I*D$	2	1.60	.26	.1863	2.66
		.004	ΣNeg TT	9			.0640	
		- .004	ΣVV_{NW}	12			.0438	
Northwest Red	1	.005	ΣVV_W	12	1.07	.30	.1671	1.61
		.141	$\Sigma \dot{P}I*D$	2			.0440	
		.000	ΣNeg TT	9			.0053	
Four A	5	.288	$\Sigma \dot{P}I*D$	2	1.06	.29	.1655	2.73
		.003	ΣNeg TT	9			.0530	
		.000	$\Sigma VV_W \dot{P}$	12			.0005	
Four B	1	.011	ΣVV_W	12	2.10	.24	.3095	2.97
		.004	ΣNeg TT	9			.0295	
		.084	$\Sigma \dot{P}I*D$	2			.0119	
Bethel	1	.325	$\Sigma \dot{P}I*D$	2	2.23	.23	.3048	4.13
		.003	ΣVV_{NW}	12			.0407	
		.000	ΣNeg TT	9			.0141	

[1]Variable symbols and numbers are explained on page 9.
[2]Numbers in this column were provided by the screening program; they determine the relative order of importance of the variables.

(ΣVV_R) was the primary factor on three paths. An arbitrary decay function was used to decrease the sum of the precipitation intensities with time. The function is held at one for the first 2 days, reaches 0.5 on the 5th day, and levels off at 0.2 from the 9th day on. This function, used to simulate stabilization with time, decreased the probability of misclassification on seven of eight paths. This parameter is currently being refined for both wind and precipitation. Temperature appears to be an important secondary factor. It was the second most important variate on three paths.

The stepwise program is affected by correlation between independent variables. Therefore, the order of importance (table 3) is relative. The primary validity of the variables selected is given by the probability of misclassification in column 7 of table 3. Variables contributing the least toward the explained variance have coefficients near zero. Because there is some correlation between variables, coefficients may be negative in a few cases, even though the physical effect of the variable is assumed to be positive.

The multivariate analysis indicates that (1) precipitation intensity, (2) windspeed resolved to an optimum direction for each path, and (3) temperature can be used to predict the likelihood of avalanches. Even more important, these 3

variables predict avalanche activity on the test paths more accurately than do all 13 variables combined.

The variables and order of importance are different for different paths. Paths with a high frequency of occurrence are less affected by low temperatures than are paths that run less often, which is no surprise since it takes time to change snow structure. The effects of rapid temperature changes on avalanche release were not examined due to insufficient data. In this regard, one must realize that rapidly falling temperatures occur almost every afternoon, but avalanches do not.

Applications

The technique and analysis developed in the second phase of this study can be applied to weather and avalanche data anywhere. Weather factors dominating avalanche activity at the Colorado study area will probably be key factors in other areas where dry snow avalanches are the main problem. The specific coefficients derived in this study will be different at other locations, but the magnitude of these differences is not presently known.

Current plans call for testing the three-variable model by using the eight avalanche paths used in the second phase of this study as an index of avalanche activity in the 100-square-mile area between Arapaho Basin and Berthoud Pass. The response from the index group resembles the occurrence pattern of avalanches from 40 other paths in the area (fig. 5). The probability of misclassification (column 7, table 3) indicates activity from the index group can be correctly predicted 70 to 80 percent of the time. If an independent set of data confirm this accuracy the discriminant function coefficients and variables for the index group could serve as a basis for regional avalanche warnings as well as a guide for avalanche control on the eight index paths.

The L values, or discriminant scores, could be calculated and pooled for the index paths every 6 hours to simulate avalanche activity on a real-time basis. When L exceeds the discriminant index R_o for a given path, the function predicts the path will avalanche either naturally or artificially. For example, the discriminant function for the Lift Gully in table 3 is:

$$L = 0.011(\Sigma VV_{NW}) + 0.28(\Sigma \dot{P}I*D).$$

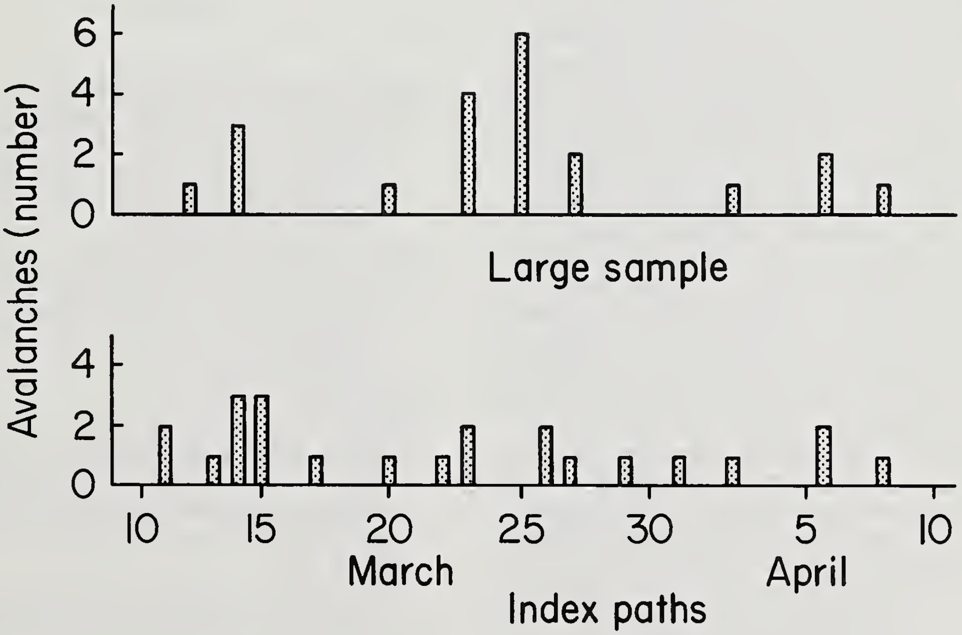

Figure 5.--Relationship between daily avalanche response from the 8 index paths and 40 other paths in the same general area, March 10 to April 10, 1965.

During one 42-hour period in December 1964, the values for the variables were 65.9 and 8.5, respectively. Substituting in the formula:

$$L = 0.011(65.9) + 0.28(8.5) = 3.1$$

R_O for this path is 2.26, the discriminant index was exceeded, and the slope avalanched. Similar calculations can be made for all index paths.

At present, individual L values are reset to zero when a slope avalanches or when it is shot with no results. The decay function reduces the sum of the maximum precipitation intensities ($\Sigma\dot{P}I$) with time. Wind and temperature could be treated in the same manner, so that L for all paths and therefore L - R_O, which represents the likelihood of avalanching, would fluctuate through periodic cycles simulating avalanche activity in the region.

Summary and Implications

The storm index developed and tested in the first phase of the study consists of the sum of the maximum 3-hour precipitation intensities multiplied by a constant for excessive windspeed ($\Sigma\dot{P}k$). It predicts the number of avalanches expected on 23 paths in Colorado's Front Range during storms. It could be used as an objective guide for issuing regional avalanche warnings. Its main limitations are: (1) it can be used only during precipitation periods, and (2) it contains no provision for a decrease in avalanche hazard during and following storms. With modifications, it can probably be used at other mountain locations where dry snow avalanches are the primary problem. An identical model made with the same weather data but based on avalanche activity from 23 **uncontrolled** paths yielded poor results. It is therefore recommended that similar models developed at other mountain areas be based on avalanche activity from paths which are controlled.

The three-variable model developed in the second phase uses maximum precipitation intensity, windspeed and direction, and temperature to predict the likelihood of avalanches on eight controlled paths in the Berthoud-Loveland Pass area. The model is untested. If planned test results are satisfactory, this model will serve as a guide for control decisions on the eight paths. It could also provide the means for issuing a regional avalanche warning and for lifting that warning. The three-variable model is more flexible than the storm index because the calculation of L, or the likelihood of avalanching, begins when snow depth on the ground reaches a threshold depth in early winter, and continues uninterrupted until spring. The L values increase and decrease with time and avalanche activity. This model could provide a daily rating of avalanche hazard which is independent of any subjective definition of storms. The main contribution from this second phase is the technique which can be used to evaluate weather and avalanche data from any mountain area. The weather factors which were found to dominate avalanche activity in this study will probably be key weather factors affecting avalanche response at other mountain locations where dry snow is common.

Although much work remains, an objective basis for issuing regional avalanche warnings is now possible. Additional variables that would give an indication of stress conditions within the snow cover, if they can be isolated and measured, would enhance the reliability of such warnings. Until we learn more about how to isolate and measure the snow-cover features pertinent to avalanche release, any objective avalanche warning scheme will be primarily dependent on weather factors.

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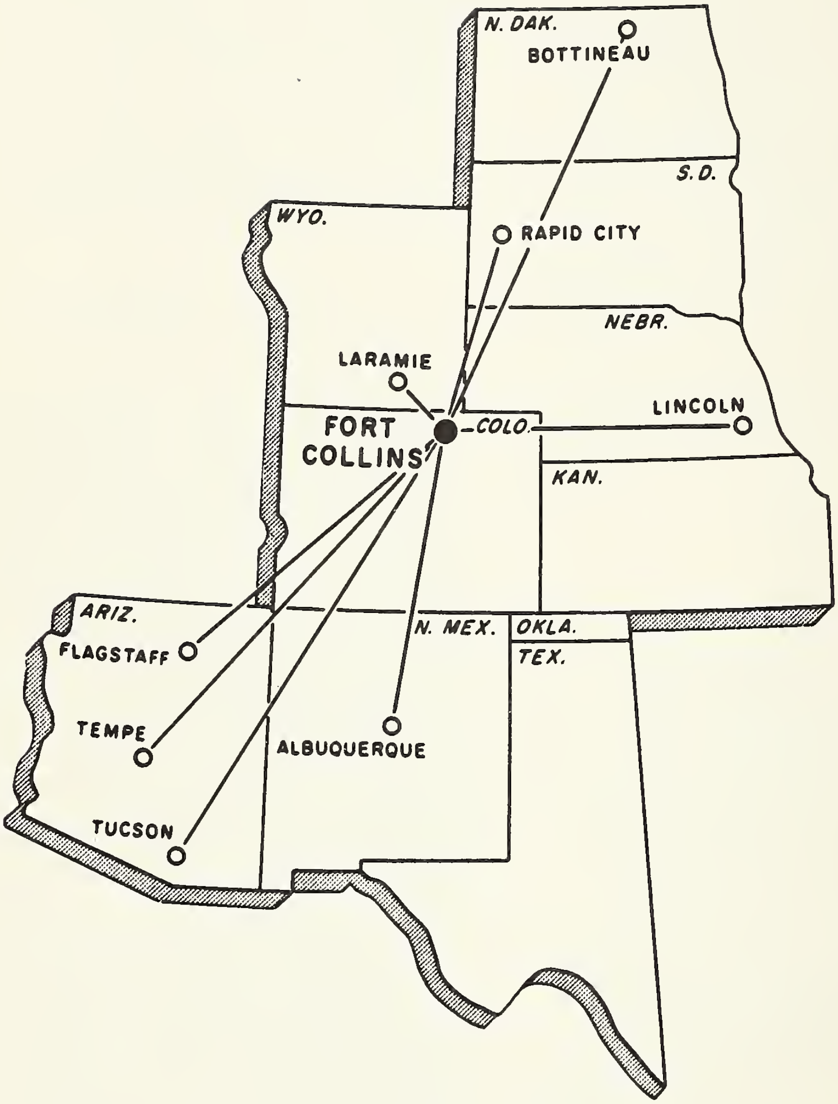

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